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The Employment, Earnings, and Income of Less-Skilled Workers over the Business Cycle

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Abstract

In this paper, I examine the effect of business cycles on the employment, earnings, and income of persons in different demographic groups. I classify individuals by sex, education, and race. The analysis uses data from the Current Population Survey's Outgoing Rotation Group data, covering the period 1979–1992, and March Annual Demographic File data, covering the period 1975–1997. Many different individual and family outcome measures are considered, including employment to population ratios, weekly earnings, hourly earnings, annual hours, annual earnings, family earnings, family transfer income, and total family income. The regression model is specified such that the key parameters measure how the labor market outcomes of less-skilled workers vary with the business cycle relative to the variability for high-skill groups. The analysis uses variation across MSAs in the timing and severity of shocks. The results consistently show that individuals with lower educational levels, nonwhites, and low-skill women experience greater cyclical fluctuation than high-skill men. These results are the most striking when examining comprehensive measures of labor force activity such as the likelihood of full-time, full-year work. Government transfers and the earnings of other family members decrease the differences between groups, resulting in more skill-group-neutral effects of business cycles on family income than on individual earnings. The paper examines the stability of these results by comparing evidence across the 1982 and 1992 recessions. The evidence suggests that the 1992 recession led to more uniform effects across skill groups than did earlier cycles.

The Employment, Earnings, and Income of Less-Skilled Workers over the Business Cycle

1. INTRODUCTION

One of the most substantial risks facing workers is the potential for job loss, either permanent or temporary. The possibility of a loss in earnings and employment is likely to be of greater concern to less-skilled workers because of difficulties in replacing lost income with savings and the earnings of secondary earners. Many government transfer programs have been established to reduce the variability of family income over the business cycle. Because of recent changes in welfare programs, however, there is some uncertainty as to the role that the safety net can and will play in future recessions.

Recent evidence suggests that state and federal policy changes are leading to increases in employment among AFDC recipients (Blank, Card, and Robins 1998). Increases in labor market attachment bring the potential for increases in family income and earnings. However, increasing labor market attachment also raises the risk of recession and loss of family income. The potential for cyclical fluctuation in earnings is very different from the relatively constant transfer that a family expected from Aid to Families with Dependent Children (AFDC).

This paper examines the impact of changes in local economic conditions on the employment, earnings, and income of individuals in different skill groups. The skill groups are defined by sex, race, and educational level. The emphasis in the paper is on evaluating the *relative* impact of cycles across these demographic groups. This is done in three parts. First, I present trends in labor market outcomes by skill group. This simple analysis provides suggestive evidence that the employment and earnings patterns of less-skilled groups show greater fluctuation in economic cycles than do the employment and earnings patterns of higher-skill groups. Second, I examine how changes in labor market outcomes vary across skill groups within metropolitan statistical areas (MSAs). In particular, I present figures comparing the changes in a particular labor market outcome over a particular period (e.g., from peak to trough of a recession) for one skill group against another within an MSA. Finally, I extend the graphical analysis to a regression framework, thereby estimating quantitatively the impact of a shock to an MSA on the relative outcomes across skill groups.

The analysis uses data from the Current Population Survey's Outgoing Rotation Group (ORG) data, covering the period 1979–1992, and March Annual Demographic File (ADF) data, covering the period 1975–1997. The advantage of the ORG data is that the samples are about three times as large as the ADF, which is particularly important when presenting results by skill groups within MSAs. The labor market outcomes that can be identified in the ORG data, however, are somewhat limited and include employment status last week and earnings last week. Ultimately, broader measures of individual and family well-being are important. The ADF provides comprehensive data on employment, earnings, and income over the past year. The analysis of the ADF data uses hourly earnings, annual hours, annual earnings, family earnings, family transfer income, and total family income. By combining evidence from the two data sources, the results tell a comprehensive story about the impact of business cycles on workers and families. The data also cover a relatively long period, allowing for examination of the recessions over three decades.

The results consistently show that the labor market outcomes of less-skilled workers exhibit more variability than those of higher-skill groups over business cycles. Nonwhites and those with lower educational levels are more impacted by changes in local economic conditions. Further, high-skill women have significantly less sensitivity to business cycles than low-skill, especially low-skill nonwhite, women. These patterns hold for both recessions and recoveries. These groups are more likely to have reductions in employment and earnings during a downturn, and are also more likely to have gains in recoveries. Examining individuals in isolation, however, gives an incomplete picture of the effect of cycles on well-being. The results also show that government transfers and the earnings of other family members decrease the differences between groups, resulting in more skill-group-neutral effects of business cycles on family income than on individual earnings.

Many previous studies have examined the effects of business cycles and local labor markets on individuals and families. That prior work generally shows that less-skilled workers are more impacted by cycles. My research contributes to the literature in three important ways. First, the focus of this paper is on comparing the responses across demographic groups. These groups are defined by sex, education, and race. Second, the paper examines a broad range of individual and family outcomes including employment, hours, earnings, and income. Most previous studies focus on one or two individual measures. The combination of detailed outcome measures and comparisons across demographic groups allows me to present a very complete picture of how families are impacted by cycles in a way that has not been generated by the existing literature. Third, the study examines whether these effects vary across business cycles. This is all done in a simple empirical framework that makes use of variation across MSAs in the timing and severity of recessions. This variation is much richer than that used in time series studies.

The focus in this paper on relative responses across demographic groups and different individual and family outcomes can be used to inform the policy process. The results shed light on particular problems that may exist for less-skilled workers, for women versus men, and for whites versus nonwhites. These differences may be due to differences in labor market attachment, industry, or geographic location. Further, the examination of different outcome measures may highlight the success or failure of particular government transfer programs designed to insure against fluctuations in income. For example, policies such as unemployment insurance and job training are geared toward individuals, and their effects will show up in individual outcomes. Other policies, such as AFDC and the Earned Income Tax Credit, are geared toward families, and their effects will show up in family income.

The study is inherently a descriptive one and does not make any attempt to causally identify why there is variation across skill groups in the relative responsiveness to cycles. Among the reasons that groups may have different responses to cycles are that they have different mobility rates and labor supply elasticities, and work in different industries and occupations. I explore why the differences occur in two ways. First, I examine the “channels” by which the differences occur by looking at wages, hours, and earnings separately and by examining the components of family income. Second, I compare the characteristics of workers in different skill groups to see if groups with higher cyclical responses are more likely to be employed in occupations and industries with more variable employment.

Section 2 provides a summary of the existing literature on the impact of local labor markets on employment, earnings, and income. Section 3 describes the data. Section 4 presents the trends in individual and family outcomes over time by skill group. Section 5 describes the empirical approach. Section 6 provides a graphical analysis of differences in responsiveness to cycles across skill groups. The main regression results are discussed in section 7. Section 8 presents conclusions.

2. PREVIOUS LITERATURE

This study has connections to many different areas of research, including the literature on wage, earnings, and income inequality; trends in employment and earnings for women; determinants of labor market outcomes and differences between groups; and worker displacement. It is not feasible, nor desirable, to present a comprehensive review of the literature. Instead, this review will focus explicitly on those studies that examine the effect of local labor market conditions on employment and income outcomes. In particular, I will focus on three features of these studies: the variables used to control for the characteristics of the area labor market, the outcome measures, and the degree to which differences across groups is explored.

The applications most relevant to this analysis include those that examine the effect of business cycles and local labor markets on employment outcomes (Bartik 1991, 1993a, 1993b, 1996; Blanchard and Katz 1992; Holzer 1991), real wages (Bils 1985; Blank 1990; Keane, Moffitt, and Runkle 1988; Solon, Barsky, and Parker 1994), racial differences in labor market outcomes (Bound and Holzer 1993, 1995), labor market outcomes of disadvantaged youth (Acs and Wissoker 1991; Bound and Freeman 1992; Cain and Finnie 1990; Freeman 1982, 1991a, 1991b), and family income, poverty, and income inequality (Bartik 1994; Blank 1989; Blank 1993; Blank and Blinder 1986; Blank and Card 1993; Cutler and Katz 1991). These studies almost universally find an important role for local labor market conditions.

The studies of disadvantaged youth relate labor market outcomes to local (typically Metropolitan Statistical Area, or MSA) unemployment rates. That literature has consistently found that higher local unemployment rates lead to reductions in employment and earnings (Acs and Wissoker 1991; Bound and Freeman 1992; Cain and Finnie 1990; Freeman 1982, 1991a, 1991b), with larger effects for blacks, younger workers, and less-educated workers (Acs and Wissoker 1991; Freeman 1991b).

The studies of family income and poverty have typically used either national (Blank 1989; Blank 1993; Blinder 1986; Cutler and Katz 1991) or regional (Blank and Card 1993) variation in unemployment rates or GNP. The studies have found a consistent negative relationship between unemployment rates and inequality and poverty. Of particular interest is Blank (1989), who disaggregates household income into many components and examines the relative cyclicality of the components. She finds earnings and capital income to be procyclical and some transfer income to be countercyclical. Overall, she finds greater variation over the cycle for those who are young, male, and nonwhite.

The literature most relevant for this study uses variation across MSAs in labor market conditions to examine labor market outcomes across different demographic groups (Bartik 1991, 1993a, 1993b, 1994, 1996; Bound and Holzer 1993, 1995). The studies by Bartik use growth in employment, changes in the manufacturing share of employment, and changes in the average wage premium implied by the area’s industry mix. Bound and Holzer (1993, 1995) use skill-group-specific measures of employment growth, using as weights the skill group's participation in each industry at the beginning of the period. The results differ somewhat across the studies, but they generally show that changes in labor demand lead to larger changes for blacks, younger persons, and those with lower levels of education. The patterns seem to hold for men and women.

Distinct from the above literature on labor market outcomes are studies that use panel data to examine the cyclicality of real wages. The literature focuses primarily on aggregate measures of business cycles (national unemployment rates or GNP growth) and examines the question, To what degree are aggregate wage fluctuations over the cycle due to changes in the composition of the work force? The results vary somewhat across the studies but generally find that the composition effect alone leads to countercyclical wage patterns. Accounting for this composition effect, wages are found to be procyclical, with greater fluctuations for those who are male, young, and working in the private sector.

Overall, these studies raise several possible explanations for the differences across groups in the sensitivity to business cycles. An often cited explanation is variation across demographic groups in mobility rates. The larger the long-run supply elasticity for the demographic group, the lower the expected effect of a demand shift on wages and employment. Those with lower rates of population mobility will have larger effects. A second explanation is that different demographic groups tend to be employed in different sectors and occupations that may be associated with greater or lesser risks of layoff.

3. DATA

The study uses the ORG and March ADF data from the Current Population Survey (CPS). The CPS ORG data set, which pools monthly survey observations, has sample sizes about three times as large as the ADF, but the labor market outcomes included in the survey are limited. I use indicators for employment last week, full-time employment last week, and earnings last week, where full-time includes those working at least 35 hours per week. The data cover 1979 to 1993, with about 325,000 observations per year.[1]

The ADF (or March CPS) is an annual demographic file that includes labor market and income information for the previous year at the individual and family level. Many different individual and family outcome measures are considered, including work at all, work full-time full-year, number of weeks worked, average hourly earnings, annual hours, annual earnings, family earnings (head and spouse), family transfer income, and total family income. All measures are annual and correspond to the calendar year previous to the survey. Full-time is defined as working at least 35 hours per week last year, and full-year is defined as working 50 or more weeks last year. The ADF data are available beginning with the 1964 survey year. Because of major changes in the survey beginning in 1976, this study uses the 1976–1998 surveys covering years 1975–1997.[2] The sample size is approximately 150,000 persons per year.

The earnings data are topcoded in both surveys. In the ORG data, weekly earnings are topcoded at $999 through 1988 and at $1,923 from 1989 on. In the ADF data, annual earnings are topcoded at $50,000 through 1981, $75,000 for 1982–1984, $100,000 for 1985–1988, and about $200,000 from 1989 on. Following Katz and Murphy (1992) and more recently Blau (1998), the earnings of topcoded individuals are adjusted to be 1.45 times the topcoded value. Beginning in 1996, instead of giving each topcoded observation the value of the topcode, the CPS assigns the mean among the sample of topcodes (by demographic group). The earnings figures can be as high as $600,000 in this period. I make no

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[1]The data are available through 1995. However, 1994 and 1995 data were dropped because the variables identifying MSAs appear to be incorrect.

[2]Prior to the 1976 survey year, weeks worked last year was a categorical variable and usual hours worked per week last year was not available. Hours worked last week is available, but is a noisy measure of hours worked last year.

adjustment for topcoding in these years. There is no apparent topcoding of family earnings or family income. Real earnings and income are constructed using the CPI-U-X1 deflator.

For most of the analysis, the microdata are collapsed into cells defined by MSA, year, and skill group. Skill groups are defined by education (either <12, 12, 13–15, 16+ or ≤12, >12) , race (white, nonwhite), and sex. The nonwhite group includes both blacks and white Hispanics. The ORG data identify 44 MSAs, while the ADF data (beginning a few years earlier) identify 35 MSAs. To better approximate labor market areas, the MSAs are combined in their consolidated MSA (CMSA) units where applicable. Examples of CMSAs include New York, Los Angeles, and Chicago. The final sample includes 35 MSA/CMSAs in the ORG data and 27 MSA/CMSAs in the ADF. For the remainder of the paper, these geographic units will be referred to as MSAs.

In 1990, the MSA sample accounts for about 60 percent of the total metropolitan population, or 50 percent of the total population. The sample accounts for virtually all of the metropolitan population in 1975. The lack of complete coverage in the later part of the period is due to the need to create metropolitan areas that are consistent geographic units over the entire period. Therefore, metropolitan areas that are added in the middle of the period, for example, are not included in the sample.[3] The median MSA in the ORG data contains about 200 observations per year, compared with about 75 observations per year in the ADF. Once the cells are further refined to skill groups, some cells get quite small. When possible, data are combined into 2-year periods to reduce the problem of small skill-group/MSA/year cells. All analyses in the paper are weighted.[4]

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[3]Considerable effort was made to insure that the MSAs were comparable units over time. For example, it is relatively common for an MSA to split into two. The split-off MSAs were combined, making the series comparable over time. However, some MSAs grow over time as additional areas are added to an existing MSA. These changes cannot be addressed. Fortunately, changes in MSA definitions occur only once per decade, following the decennial census. These “seam years” were dropped from the analysis in sensitivity tests.

[4]The CPS data are not designed to be used as an MSA sample. This can lead to significant sampling errors in the MSA/skill-group cells. This is addressed by using weights in the analysis and by making every effort to have large cell sizes (by choosing the largest MSAs, combining 2-year periods, and using relatively few skill groups).

The same sample selection criteria are applied to both the ORG and ADF data. The sample includes persons between 22 and 62 years old. The self-employed, those working without pay, and those with positive earned income but zero hours of work are excluded. Following Katz and Murphy (1992), individuals with real weekly earnings of less than $67 in 1982 dollars (i.e., one-half the value of the minimum wage assuming a 40 hour work week) are also excluded. The final sample has about 220,000 observations per year in the ORG sample and 70,000 observations per year in the ADF sample.

4. TRENDS IN LABOR MARKET OUTCOMES AMONG SKILL GROUPS

This section presents simple time series trends in labor market outcomes by education, race, and sex. The purpose is to introduce the labor market outcomes that will be used in the empirical analysis and to provide an initial description of the trends in the outcomes variables and how they vary across different groups. Using these simple figures to make comparisons across groups in their responsiveness to cycles, however, may not be possible because of the difficulties in separating secular trends from cycles. Therefore, these results should be viewed only as a first step. In the interest of space, the discussion uses only ADF data.

4.1 Definitions

Skill groups are defined by education, race, and sex. Low-skill workers are typically defined using educational level and most often include persons with less than a high school education. This analysis uses data covering a period of three decades and is concerned with making comparisons across groups over time and cycles. It is important for the analysis that the skill groups are defined to be relatively comparable over time. However, educational levels have been rising over time for all demographic groups. In the presence of rising educational levels, even if the distribution of earnings and income is unchanged over time, one would expect that the relative position of less-educated persons (e.g., high school dropouts) would decline over time. That is, over time, this group would become more and more disadvantaged.

To illustrate this point further, Figure 1 presents trends in the percentage of persons with various educational levels in the ADF sample, by race and sex. This figure shows that the percentage of persons with less than a high school education has fallen dramatically in this period. For example, between 1975 and 1997 the percentage of white men with less than a high school education declined from 25 percent to less than 10 percent. For nonwhite men, this percentage declined from 50 to 30 percent. At the same time, among whites, the percentage with a high school diploma has not changed, and the percentage with greater than a high school diploma has increased. Among nonwhites, both high school and more than high school groups are increasing. The trends are even more dramatic for women.[5]

In the presence of these increases in educational levels over this period, the main analyses in this paper will compare those with a high school education or less to those with more than a high school education. Those with a high school education or less are defined to be *less-skilled workers*. This group will be less disadvantaged than high school dropouts, however, and where possible I examine outcomes across all four education groups (<12, 12, 13–15, 16+).[6]

4.2 Trends in Employment, Earnings and Income Using ADF

Figure 2a presents trends in employment to population ratios for men for between 1975 and 1997 by race and education. There are two definitions for the employment to population ratios. The *Any-work EPOP* is the employment to population ratio where a person is considered employed if he worked at all last year. The *FTYR EPOP* is the employment to population ratio where a person is considered employed

[5]Beginning in the 1992 survey, the CPS records the degree earned rather than the years of schooling completed. As is evident in the figure, this decreases the percentage with a high school diploma and increases the percentage with greater than a high school diploma.

[6]An alternative approach is to define skill groups by their relative position in the earnings or wage distribution (e.g., less than the 20th percentile). Because this analysis is not limited to workers, skill groups would have to be assigned using *predicted* wages. This may be examined in future work.

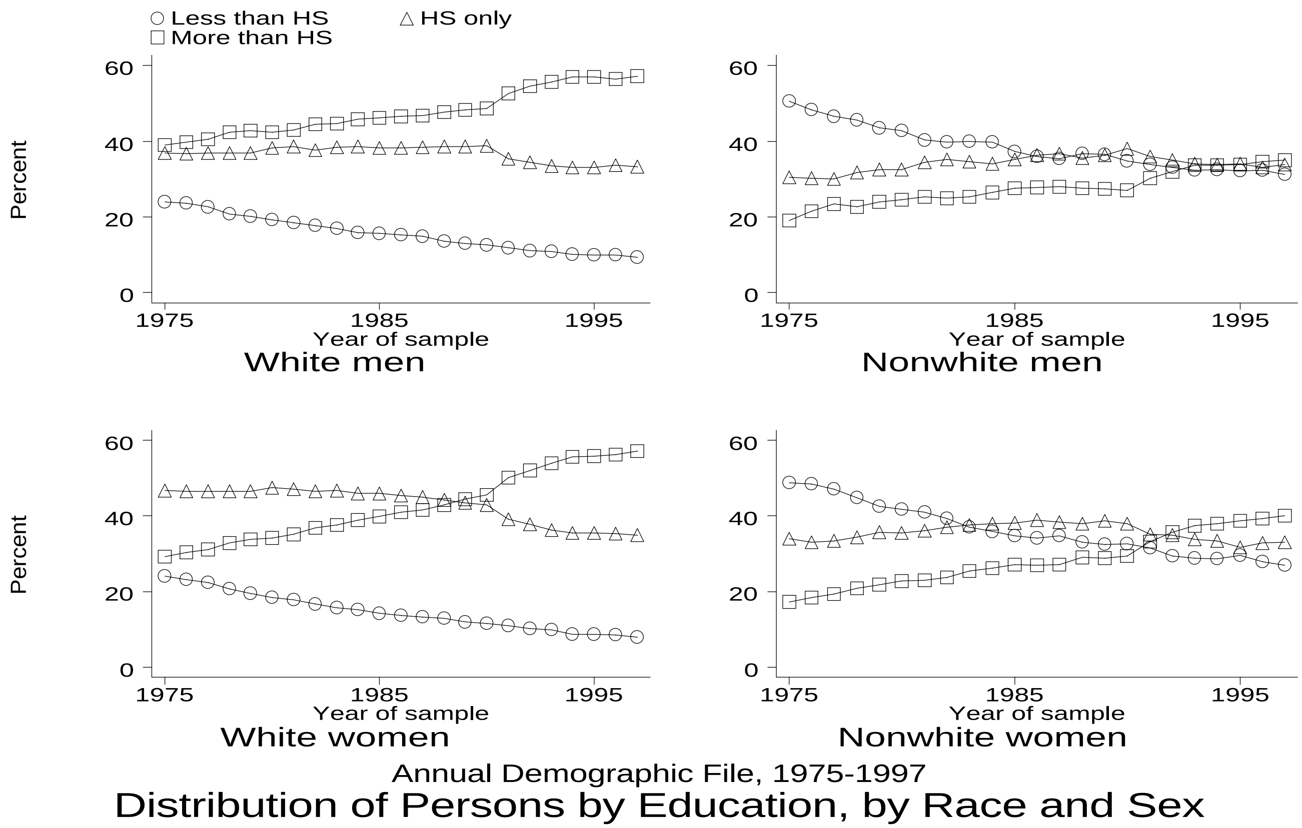
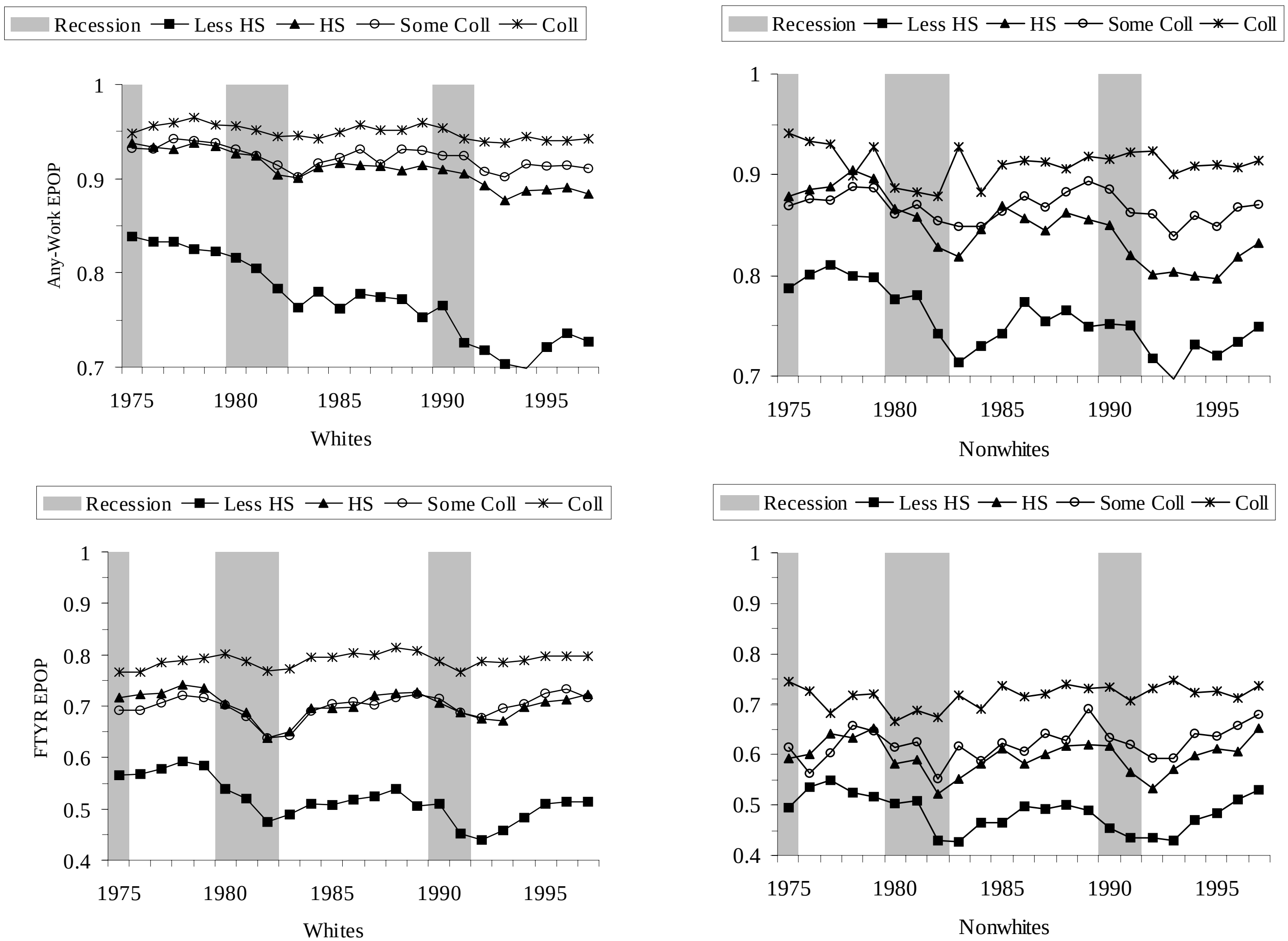

Less than HS
HS only
More than HS
Percent
0
20
40
60
1975
1985
1995
Year of sample
White men
Nonwhite men
White women
Nonwhite women
Annual Demographic File, 1975-1997
Distribution of Persons by Education, by Race and Sex

Figure 1

Figure 2a
Annual Employment Outcomes, By Race and Education, Men (ADF File)



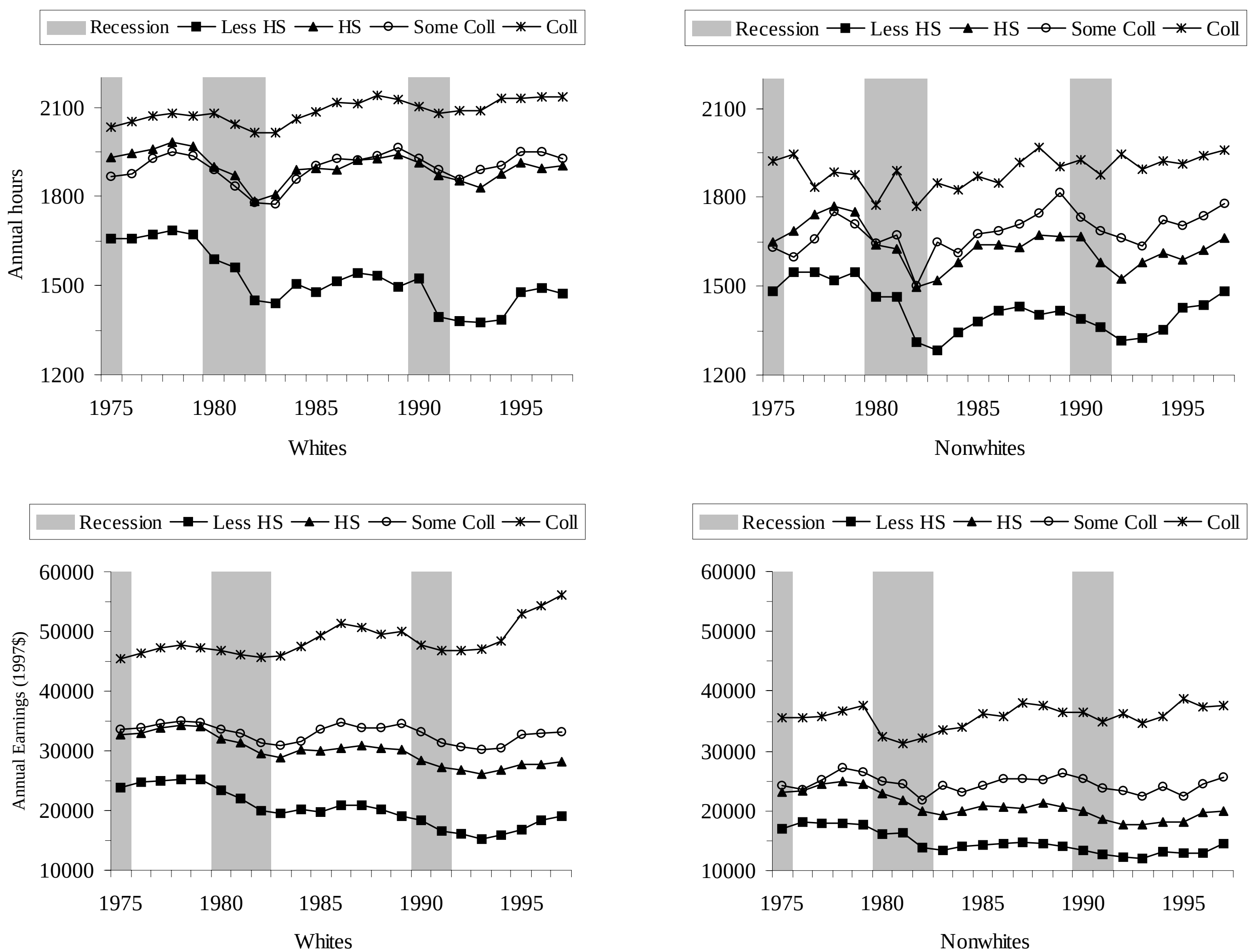
if he worked full-time (at least 35 hours) and full-year (at least 50 weeks) last year. In Figure 2a, the left two graphs are for whites and the right two graphs are for nonwhites; the top graphs present the *Any-work EPOP* and the bottom graphs present the *FTYR EPOP*. Shading indicates periods of recession. National unemployment rates peaked in 1982 and 1992.

Several observations stand out in these simple figures. As expected, EPOP ratios are higher for those with higher educational levels. Among less-educated men, nonwhites tend to have higher EPOP ratios than whites. A striking trend in the figure is the declining employment of population ratios among men with less than a high school education. By the mid-1990s, fully 30 percent of men are not working *at all* over the year. This is undoubtedly due in part to the changing composition of the lowest education group over this period.

The graphs also provide insight into the impact of cycles on different groups. The figures suggest that employment rates of those with lower educational levels and nonwhites exhibit more cyclical variation. There seems to be more cyclical fluctuation in the full-time employment rates (*FTYR EPOP*) than the any-work employment rates (*Any-work EPOP*). For nonwhites with less than a high school education, the *Any-work EPOP* also varies significantly over the cycle. This is striking given that the measure is any work in the entire calender year. The high rates of nonwork in the trough of the recession are consistent with the persistently high unemployment rates for this group. Note that some of the variability in the measures for nonwhites reflects small sample sizes, especially for higher education groups.

Figure 2b presents trends in annual hours and earnings for the same groups of men. The figures are arranged as above, with white men on the left and nonwhite men on the right. The top row shows mean annual hours worked and the bottom row shows mean annual earnings. These earnings and hours figures are averages over all individuals in the race-education-sex-year group, and they include workers

Figure 2b
Annual Hours and Earnings, By Race and Education, Men (ADF File)



and nonworkers. Therefore, the change in earnings is comprehensive and reflects changes in hours, weeks, and hourly wages, as well as changes in the composition of the work force.

In general, the pattern for annual hours worked is similar to the trends for the EPOP ratios. These figures show that, to a greater extent than in other measures, both annual hours and real annual earnings show cyclical variation for college-educated white men. Though the average hours and earnings of less-educated individuals also show cyclical variation, the *relative* variability of low versus high education groups is less dramatic than the employment figures. In graphs not presented here, the variation in annual hours worked comes more from variation in weeks worked per year than from hours worked per week. That may be due to measurement error in hours worked per week, or it may reflect the nature of employment reductions that firms engage in.[7]

Figures 3a and 3b present corresponding results for women. These graphs show that employment and earnings for women are increasing secularly over this period for all groups, but at a substantially slower rate for nonwhite women and women with low educational levels. These trends are so strong that it is difficult to make any inferences about the variation over the business cycle.

Although not shown here, family earnings and family income also show cyclical variation. Family income, and to a lesser extent family earnings, shows less variability across demographic groups compared with the fluctuations in individual earnings. Our empirical model will explore the reasons for this difference.

5. EMPIRICAL MODEL

The goal of this analysis is to estimate how individuals in different demographic groups are affected by changes in macroeconomic conditions. One approach to estimating this effect is to take the

[7]Figure 2b shows that average earnings for college-educated white men increased substantially starting in 1995. This is due to the change in the topcoding in the CPS. The results are not sensitive to dropping these years.

Figure 3a
Annual Employment Outcomes, By Race and Education, Women (ADF File)

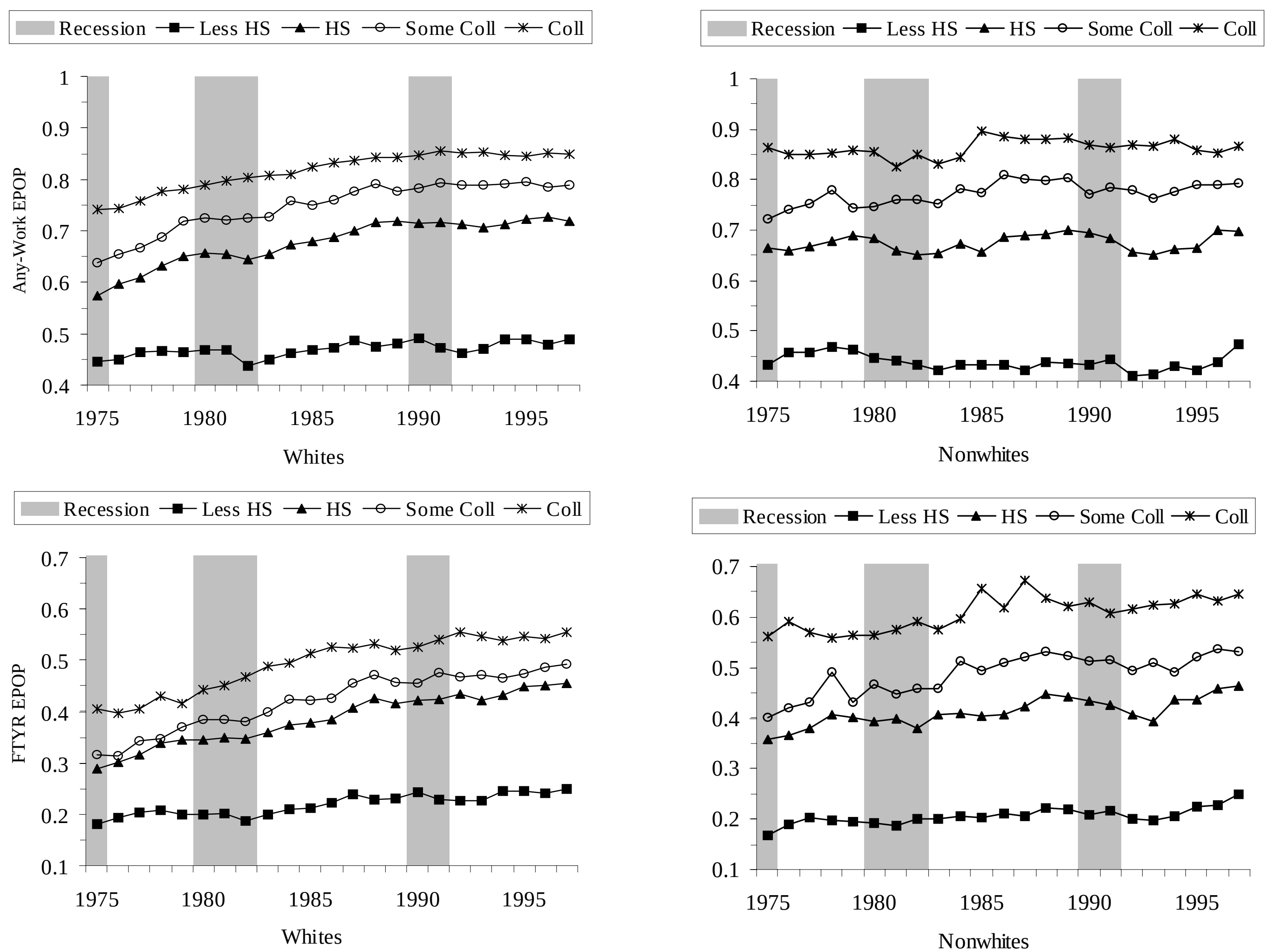
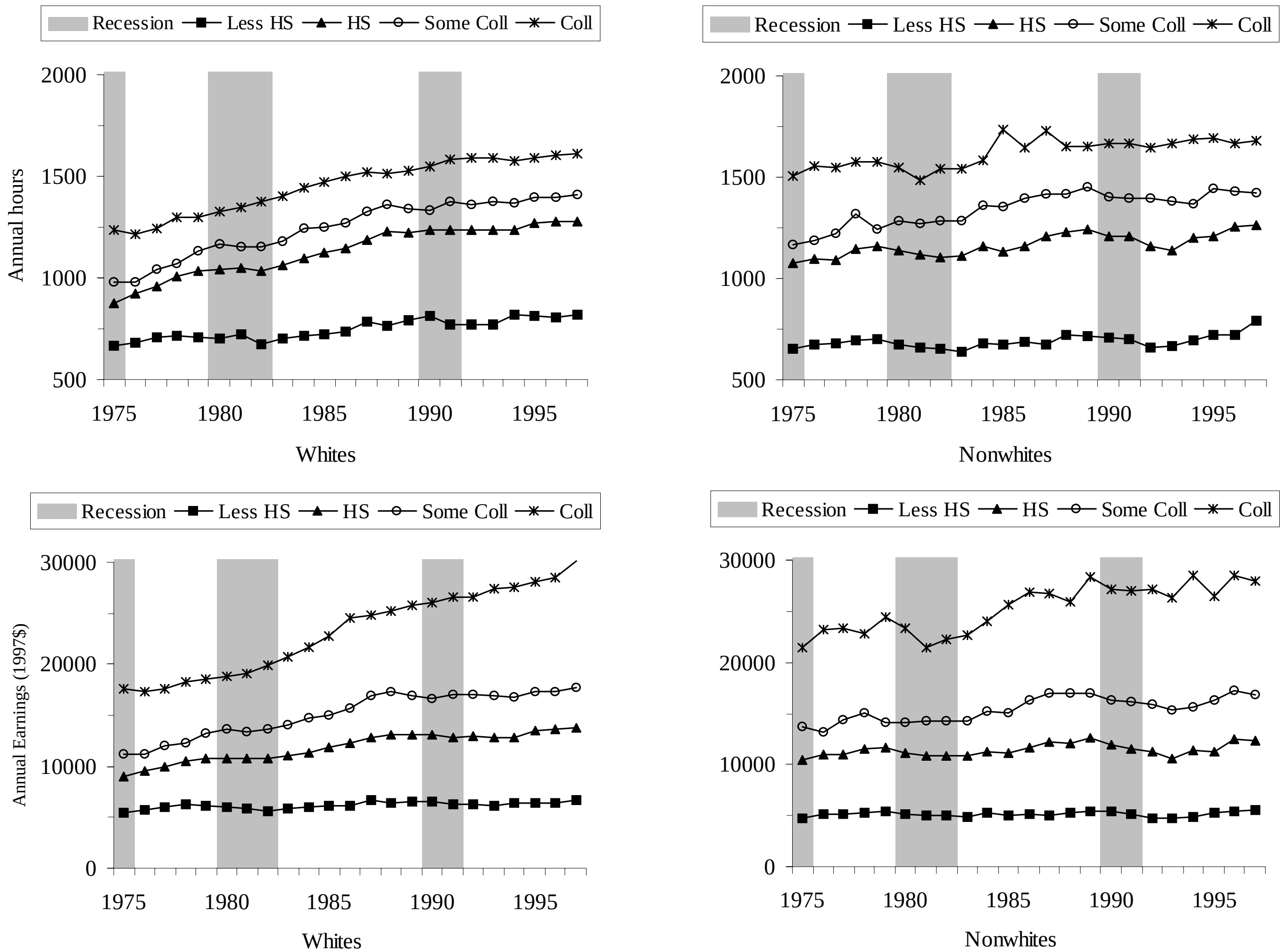


Figure 3b
Annual Hours and Earnings, By Race and Education, Women (ADF File)



time-series trends presented above and regress the outcomes on a measure of the business cycle such as the unemployment rate. This approach is not taken here for two reasons. First, aggregate measures of business cycles do not necessarily capture the relevant cycle if there is area variation in the timing or severity of the cycle. Second, the unemployment rate (or some other aggregate measure of employment) can be mechanically related to the dependent variable (e.g., the EPOP ratio for less-skilled persons). This reflection or endogeneity problem makes the interpretation of such estimates difficult. One approach used in the literature is to instrument for the unemployment rate (Bound and Holzer 1993, 1995). As an alternative, this analysis treats the shock to a local area as unobserved and compares the response to the shock among different groups. This avoids the reflection problem and has the added advantage of differencing out an MSA effect. All the comparisons across groups are made within MSAs, which takes advantage of the wide regional variation in the timing and severity of recessions.

For this and all remaining analyses in the paper, I start by collapsing the data into cells defined by MSA (*m*), time (*t*), and skill group (*j*). Let y_{jmt} be the mean of a given labor market outcome for group *j* in area *m* in year *t*. Suppose one could observe some exogenous measure of the business cycle in the MSA in time t, represented by y_{mt}. Putting the variables y in logs, one could characterize the log of the mean labor market outcome for group *j* in MSA *m* in period *t* by the following equation:

$$\ln(y_{jmt}) = \alpha_{0j} + \alpha_j t + \delta_t + \mu_m + \gamma_j \ln(y_{mt}) + \varepsilon_{jmt} \qquad \textbf{(1)}$$

Here, the labor market outcome is specified to be a function of a fixed skill group effect (α_{0j}), a skill-group-specific trend (α_j), a fixed time effect (δ_t), a fixed MSA effect (μ_m), a measure of the MSA cycle y_{mt}, and a random component υ. Note that the coefficient on y_{mt} varies with skill group so the effect of MSA fluctuations can differ across the groups. The key parameters are the γ_j's.

Suppose for each MSA and skill group, the equation is differenced over some time period *t*. Using the symbol Δ to represent the change in a variable, the equation becomes

$$\Delta\ln(y_{jmt}) = \alpha_j + \upsilon_t + \gamma_j \Delta\ln(y_{mt}) + \varepsilon_{jmt} . \qquad \textbf{(2)}$$

In the transformed equation, $\Delta\ln(y_{jmt})$ is the change to the labor market outcome for group *j* in MSA *m*, between $t-1$ and *t*. The term $\Delta\ln(y_{mt})$ represents the shock to a particular MSA in time *t*. Note that in this equation, the fixed MSA effect and the fixed group effect drop out.[8]

The problem with estimating this equation is finding an exogenous measure of the shock $\Delta\ln(y_{mt})$. The approach used here is to treat the shock as unobserved and estimate each of the $\Delta\ln(y_{mt})$ as parameters. I therefore estimate the following equation:

$$\Delta\ln(y_{jmt}) = \alpha_j + \gamma_j \beta_{mt} + \varepsilon_{jmt} . \qquad \textbf{(3)}$$

This is a very simple equation. The β_{mt} parameters capture the shock to MSA *m* in period *t* and are just coefficients on dummy variables for each MSA-time period. There are a total of M*T parameters for the shocks where M is the total number of MSAs and T is the total number of time periods. Overall, there are J*M*T observations where J is the total number of skill groups. The parameters for the shock can be estimated because of the multiple skill groups for each MSA-year. The model is identified by the assumption that the responsiveness across skill groups γ_j is constant across MSAs.[9]

The main interest of the paper is to compare the relative responsiveness across groups. This is captured by the parameters γ_j. The model can be extended to look for structural changes in the intercepts (skill-group trends) and slopes (skill-group responsiveness to cycles) over time. The approach is a simple way to allow for comparisons between multiple skill groups over multiple time periods.

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[8]Further, the fixed time effect and random error term have been transformed to be the first difference of the original terms.

[9]In practice I have eight skill groups, which turns out to be more than enough to estimate the parameters precisely. Note that the time effects λ_t are subsumed in the MSA-time–specific time effects. The MSA shock parameters may not be consistent because with each additional period T, M (number of MSAs) additional parameters must be estimated.

The analysis will use many alterative individual and family outcomes to fully characterize the impact of cycles on different groups. Accordingly, the model in equation 3 is estimated for each of the outcomes of interest. First this estimation is done one equation at a time. In this estimation, the parameters capturing the skill group response to the shock (γ) have to be normalized to fix the scale of the estimated shock parameters (β). We choose a "reference" skill group and normalize the γ for that group to 1. The parameters for the other skill groups are interpreted as the response relative to the response for the reference group. In addition, the intercept for the reference group is set to 0, so the intercepts for the other skill groups are interpreted as the average trend for group *j* relative to the trend for the reference group.

This estimation does not take account of the fact that the MSA-time "shocks" (β_{mt}) enter each of the labor market outcome equations. Therefore I also estimate the models by pooling the equations and constraining the β_{mt} to be equal across the equations. This "pooled" model has three advantages. First, only one normalization on the γ's is necessary across all the equations. We can therefore examine not only how the sensitivity to cycles varies across groups but how it varies across different outcome variables. Second, there may be efficiency gains to accounting for the common parameters across the equations. Third, conceptually it is attractive to think of a single "shock" to an area which is then filtered down to different outcomes (e.g., hours, earnings, income) and different groups.[10]

Although the model in equation 3 is presented in logs, in practice I examine the models using both changes in logs and changes in levels. The change in the logs is attractive because of the interpretation as percentage changes in the variable. In practice, we do not know if the correct form for the model is in levels or logs. Because the mean levels of the outcomes vary substantially across the groups, the estimates of the γ can be significantly biased toward finding greater responsiveness to cycles

[10]Note that even though the shocks are equivalent across equations, the parameters cannot be "added up" across equations. That is because the dependent variable is the change log of the *mean* within a cell. Specifically, even if $y = y_1 * y_2$, the log of the mean of y does not equal the log of mean of y_1 times the log of the mean of y_2.

for less-skilled groups if the model is misspecified.[11] We will investigate the sensitivity to this assumption in the estimates below.

These regressions are estimated using both the ORG and ADF data. Skill groups are defined by education, race, and sex. There are eight skill groups (2 sex * 2 race * 2 education). With the exception of average hourly earnings (which is averaged over workers only), all variables are constructed as means over the entire population (workers and nonworkers) in these cells using the CPS sample weights. To increase cell sizes (which is important for nonwhites), the data are grouped into 2-year periods.

The variables in the analysis include employment rates, hours worked, earnings, average hourly wage, head's earnings, spouse's earnings, transfer income, and other family income. In each case the cell means are constructed using the sample of individuals (as opposed to families) and their characteristics (e.g., sex, education, race). Therefore, the entire analysis is based on individuals, even though some of the measures are "family"-based measures. I do this so that I can directly compare the results for individual and family outcomes. The alternative is to create cells using observations on families, using the head's characteristics to define the cell. This makes it difficult to connect the individual and family measures.[12]

The two education groups are those with a high school education or less and those with more than a high school education. The choice of two education groups (versus the four groups used in the aggregate analysis) is made for two reasons. First, and most important, I argued above that with increases

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[11]To see this point, assume that the true model is linear in the changes in levels. Then (dropping the MSA subscript) equation 3 becomes $\Delta y_{jt} = a_j + g_j \Delta y_t + e_{jt}$. Let y_j denote the mean level of y_{jt} and y denote the mean level of y_t. Then the equation can be transformed to be $\Delta y_{jt}/y_j = a_j/y_j + g_j*(y/y_j)\Delta y_t/y + e_{jt}/y_j$. Using an approximation for the log, this implies that $\Delta\log(y_{jt}) = \alpha_j + \gamma_j \Delta\log(y_t) + \varepsilon_{jt}$, where $\gamma_j = g_j*(y/y_j)$. So if group j has a low mean of the variable y, then the estimated γ_j will be greater than 1 even if (the true) $g_j = 1$. I thank Joe Altonji for pointing this out and Dave Card for helping to formalize it.

[12]In an earlier version of this paper, I followed Karoly (1992) and others and created adjusted family measures by dividing by the family's poverty threshold. This adjusts for family size using the implicit equivalency scales which account for age structure and economies of scale. Neither of these adjustments changed fundamentally the results from what is reported here.

in educational levels, the group with less than a high school education is becoming more disadvantaged over time. This showed up quite dramatically in the simple trend graphs presented above. By choosing somewhat broader education classes, I hope to minimize the problems with making comparisons over time with a group whose composition is changing. The down side of this approach is that the "low" education group is not that low, and this will probably attenuate the differences between low- and high-skill groups. Second, the use of four education groups leads to very thin cells, especially with nonwhites.

6. GRAPHICAL ANALYSIS OF DIFFERENCES ACROSS LOW- AND HIGH-SKILL GROUPS

Before presenting the results from the empirical model, this section explores differences across groups in their response to the 1982 recession. Specifically, the graphs plot the change in a labor market outcome for a particular low-skill group [$\triangle\ln(y_{jmt})$] against the change in the same labor market outcome for a high-skill "reference group" [$\triangle\ln(y_{rmt})$]. This approach can generate simple comparisons between the sensitivity of employment, earnings, and income of less-skilled groups to more-skilled groups. The presentation here will be limited to the ADF data.

In particular, I look at changes between the trough and peak of a given cycle. All figures in this section use the 1982 recession as the cycle, measured as the change from 1979 (previous peak) to 1982 (tough). The 1982 recession is chosen because it was the most severe recession in the period covered by the CPS data. The reference group for all figures is more-educated white men (those with greater than a high school education), chosen because they appear to be the group with the least sensitivity to cycles. This approach is best applied to groups that are not experiencing significant trends over time. It can be difficult to extract the cycle from the trend in this simple analysis. Consequently, in this section I present graphs only for men. The regression results, presented in the next section, provide estimates for all eight skill groups.[13,14]

All of the graphs have the same form. First consider the top left graph of Figure 4. Each point on the graph represents a pair of outcomes for the low-skill versus the high-skill groups for an MSA. On the y-axis is the change in the log of the *Any-Work EPOP* (last year) for white men with a high school education or less (the low-skill group). On the x-axis is the change in the log of the same EPOP measure for the reference or high-skill group defined as white men with more than a high school education. The figures differ only in the choice of low-skill group and labor market outcome. The top right graph compares the change in *Any-Work EPOP* for nonwhite men with a high school education or less to the reference group. The bottom row of graphs presents the same analysis for the *FTYR EPOP*. The points on the graph are weighted to reflect the size of the MSA. The larger the circle, the larger the MSA.

Each graph includes a 45 degree line to make the comparison between groups easier. If the points generally lie below the 45 degree line, than the percentage change in the outcome for the less-skilled group is greater (more negative) than the change in the outcome for the high-skill group. If the points are clustered on the line, then the responses are similar. A point above the 45 degree line means a larger response among the high-skill group than among the low-skill group.

One advantage of this approach is that it makes use of rich variation across labor markets in the United States. As an illustration of this, Table 1 compares the outcomes across MSAs in the 1982 and 1992 recessions. In particular, I measure the change in the log of the male employment to population ratio for any work (*Any-work EPOP*) last week based on the ORG data for each MSA for 1979–1982 and

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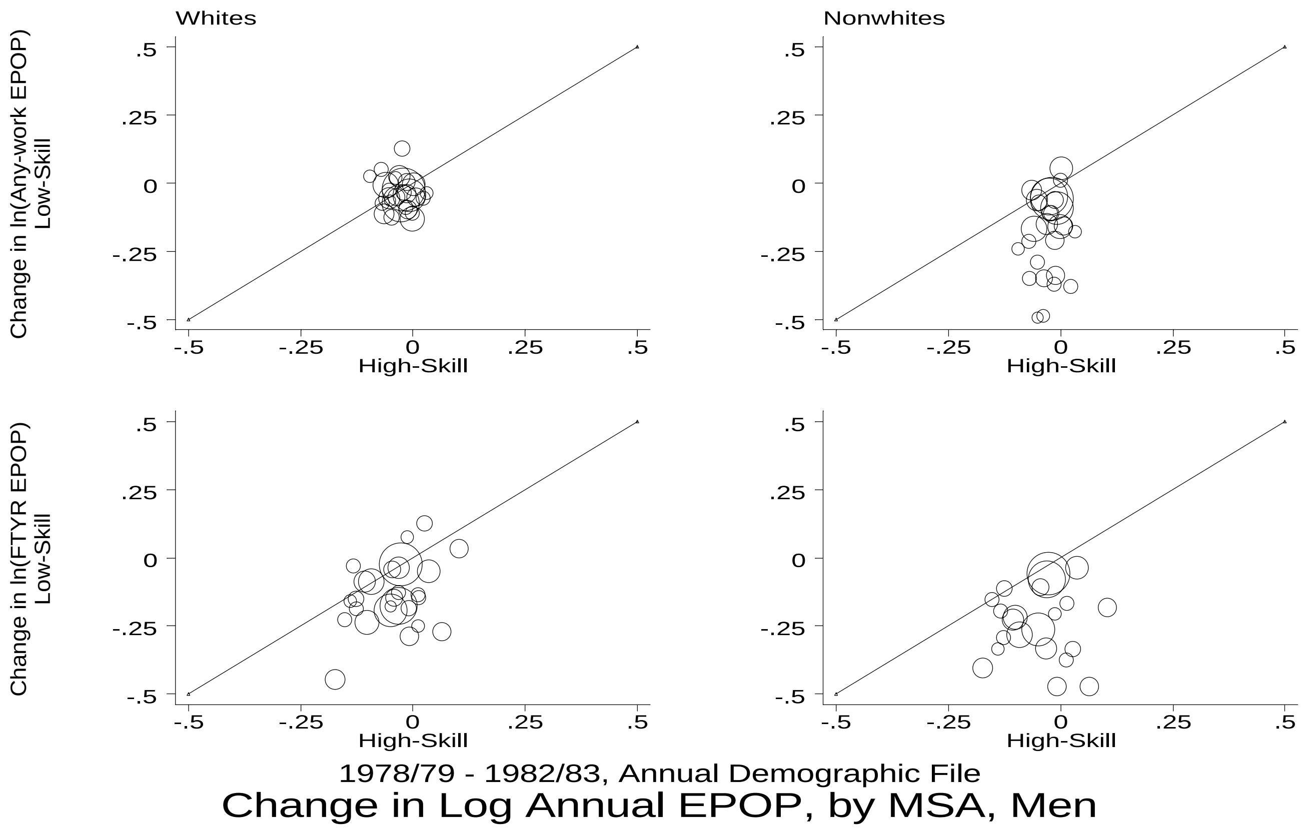
[13]One could in principle de-trend the data for women before plotting the data. Another possibility is to control for the trend by using high-skill women as the reference group for women. Both of these approaches were implemented but, in part to keep this section brief, the discussion of women is postponed until the regression results.

[14]As mentioned above, the CPS data are combined into 2-year periods to increase the number of observations in each cell. Still, some of the nonwhite skill groups have very few observations in some of the smaller MSAs. For the graphs, a cell is only included if there are at least 20 observations per cell. On average, this drops about five MSAs on the nonwhite graphs.



Whites
Nonwhites
Change in ln(Any-work EPOP)
Low-Skill
Change in ln(FTYR EPOP)
Low-Skill
.5
.25
0
-.25
-.5
-.5
-.25
0
.25
.5
High-Skill
1978/79 - 1982/83, Annual Demographic File
Change in Log Annual EPOP, by MSA, Men

Figure 4

TABLE 1
Change in the Log of Male Employment to Population Ratio in Selected MSAs, 1979–1982 and 1989–1992

Change in the Log of Male *Any-work EPOP* between 1979 and 1982

Large Reduction		*Small Reduction*	
Detroit	-0.14	Denver	-0.05
Pittsburgh	-0.13	Washington, DC	-0.03
Columbus, OH	-0.12	San Francisco	-0.03
Milwaukee	-0.11	New York	-0.02
Cleveland	-0.10	Boston	-0.01

Change in the Log of Male *Any-work EPOP* between 1989 and 1992

Large Reduction		*Small Reduction*	
New Orleans	-0.15	Miami	0.00
San Diego	-0.09	Kansas City	0.00
Boston	-0.08	Detroit	0.01
New York	-0.07	Cleveland	0.02
San Francisco	-0.07	Houston	0.02

Notes: Author's tabulations of CPS ORG data. *EPOP* is defined as the weighted number of men working last year over the weighted male population in the MSA. The sample includes all men between 22 and 62 years old. We exclude those working without pay, the self-employed, and those with weekly earnings less than $67 in 1982 dollars. For more detail on sample selection, see text.

1989–1992. For each of the two periods, the table presents the MSAs with largest and smallest percentage changes over the period. The 1982 recession hit the industrial Midwest hardest. For example, Detroit, Pittsburgh, and Cleveland had reductions on the order of 10 to 15 percent, while San Francisco, New York, and Boston experienced reductions of only 1 to 3 percent. In the 1992 recession, on the other hand, reductions on the order of 7 to 10 percent were experienced in San Diego, Boston, and New York, and the effect in the industrial Midwest was relatively mild.

Returning to Figure 4, several observations can be made. The *Any-work EPOP* graph shows that white men with low educational levels have fluctuations in employment rates that are fairly similar to white men with high educational levels. Most of the observations are clustered on the 45 degree line. The same is not true for nonwhite men. The figures on the right suggest that nonwhite men are significantly more impacted by the negative shock in this period than is the reference group. Note that almost all of the observations lie below the 45 degree line. In many cases the response for less-skilled nonwhite men is many times larger than the change for the reference group. Using *FTYR EPOP*, both white and less-skilled nonwhite men appear to be more negatively impacted by the 1982 recession than more-skilled white men. Within the less-skilled group, nonwhites appear to be significantly more affected than whites. The difference between the races is particularly evident with the *Any-work EPOP*.

Figure 5 repeats the analysis and compares the change in the log of mean annual hours worked (top row) and mean annual earnings (bottom row) for low-skill and high-skill men. Recall that annual earnings are averaged over both workers and nonworkers and thus reflect changes in employment, hours per week, and wages. This figure shows that white and (especially) low-skill nonwhite men have larger reductions in hours and earnings than more-educated white men. These patterns are similar to those found with the *FTYR EPOP*.

In figures not shown here, family income and family earnings also show greater responsiveness among less-skilled men. The differences between groups appear to be smaller than for annual earnings.

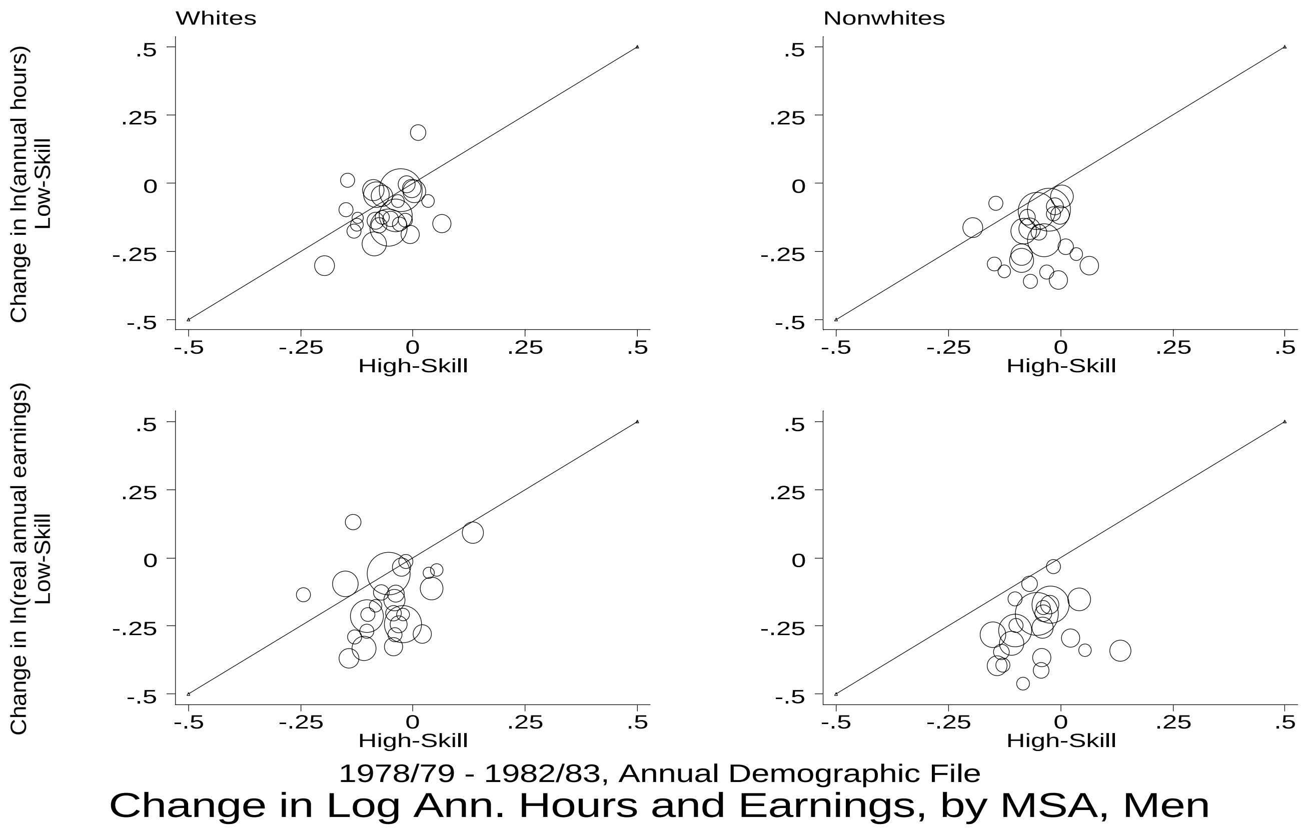

Whites
Nonwhites
Change in ln(annual hours)
Low-Skill
Change in ln(real annual earnings)
Low-Skill
.5
.25
0
-.25
-.5
High-Skill
1978/79 - 1982/83, Annual Demographic File
Change in Log Ann. Hours and Earnings, by MSA, Men

Figure 5

This is likely to reflect the ongoing increases in employment and earnings among married women, the presence of secondary workers entering the labor market to replace the recession-induced lost earnings of the primary earner, or the countercyclical effect of government transfers for low-skill groups. These patterns are explored further below.

7. REGRESSION RESULTS

The preliminary analysis above shows that low-skill men were more impacted by the 1982 recession than were high-skill men. Within skill groups, nonwhites seem to be affected more adversely than whites. These results, while illustrative, are somewhat qualitative and may be sensitive to the presence of trends for skill groups. In addition, the results speak to one particular time period and do not take full advantage of the differences in the timing of cycles across areas. This section extends the analysis by providing estimates of the empirical model in equation 3 using the full time periods covered in the data. This approach uses year-to-year changes to take full advantage of the variation in the timing of the economic changes across areas.

The observations for the regressions are the cells defined by skill group, MSA, and time. There are six time periods and 35 MSAs in the ORG data, and ten time periods and 27 MSAs in the ADF data.[15] With eight skill groups, this yields a total of 1,680 observations in the ORG and 2,160 observations in the ADF. The reference group for all regressions is more-educated (>12 years of school) white men. All models are estimated with weighted nonlinear least squares with weights constructed as the population

[15]For the analyses of both data sets, the data are combined into 2-year periods. The ORG data cover 1979/80–1991/92. 1993 was dropped because there was no year to pool it with. The ADF data cover 1975/76–1995/96, with 1997 dropped. After differencing the data, there are six time periods in the ORG (1981/82–1991/92) and ten time periods in the ADF (1977/78–1995/96). By combining two years, the resulting first differences span on average a 2-year change.

count of the cell. The precision of the estimate of the dependent variable varies inversely with the size of the cell, and the weights downweight the small cells. No cells are dropped from the analysis.

7.1 Results for Weekly Measures Using ORG Data

We begin by presenting estimates using the ORG data and estimate each labor market outcome equation separately, without accounting for common MSA shock across the equations. The results for these "single equation" estimates appear in Table 2. Each column in the table corresponds to estimates for a different equation, and they differ only in the definition of the dependent variable. The table reports the parameter estimates for the γ's (relative impact of the shock across skill groups). All other parameters are suppressed from the table. Because the MSA-time shock, β_{mt}, is unobserved and estimated as a parameter, some normalization must be made to fix the scale. In these initial regressions where each equation is estimated separately, we normalize the parameter for the impact of the cycle on the reference group (more-educated white men) to 1 (γ_1=1). The parameters for the other skill groups are interpreted as the response relative to the response for high-skill white men.

The ORG includes data on work status last week. Table 2 shows three measures. The *Any-Work EPOP* is the employment to population ratio where a person is considered employed if he/she worked at all last week. The *FT EPOP* is the employment to population ratio where a person is considered employed if he/she worked full-time (at least 35 hours) last week. Finally, mean real weekly earnings are used. Columns 1 and 2 present estimates where the EPOP is specified as changes in logs. Columns 3 and 4 estimate these models using changes in levels of EPOP. Column 5 presents estimates for changes in log weekly earnings. The statistical significance of the parameters is determined by testing whether the coefficient is significantly different from 1 (e.g., no differences across groups).

The results in columns 1 and 2 show sizable and statistically significant differences in the responses to cycles across skill groups. The results in column 1 show that, for a given shock, the fluctuation in the *Any-work EPOP* is 1.4 times greater for low-skill white men and almost 4 times greater

TABLE 2
Regression Results Using CPS ORG
Coefficients on MSA Shock

	(1) *Any-work EPOP (log)*	(2) *FT EPOP (log)*	(3) *Any-work EPOP (level)*	*(4)* *FT EPOP (level)*	*(5)* *Mean Weekly Earnings (log)*
Skill Group					
High educ (>12) white men	1	1	1	1	1
High educ (>12) nonwhite men	1.28	1.73	1.30	1.34	1.46
	(0.47)	(0.51)	(0.28)	(0.25)	(0.24)
High ed (>12) white women	0.56*	0.90	0.57**	0.52**	0.85
	(0.19)	(0.23)	(0.11)	(0.10)	(0.11)
High ed (>12) nonwhite women	1.21	1.61	1.09	1.10	1.01
	(0.44)	(0.47)	(0.26)	(0.23)	(0.21)
Low ed (≤12) white men	1.36	1.45	1.29	1.35*	1.22
	(0.28)	(0.31)	(0.17)	(0.16)	(0.14)
Low ed (≤12) nonwhite men	3.88**	3.51**	2.95**	2.77**	1.99**
	(0.69)	(0.66)	(0.35)	(0.30)	(0.22)
Low ed (≤12) white women	1.53	2.38**	0.82	0.63**	0.94
	(0.29)	(0.44)	(0.13)	(0.11)	(0.12)
Low ed (≤12) nonwhite women	5.42**	4.49**	1.44*	1.12	1.49**
	(0.91)	(0.81)	(0.22)	(0.18)	(0.18)
N	1680	1680	1680	1680	1680
R^2	0.39	0.38	0.40	0.39	0.47

Notes: Each column is a separate regression where the dependent variable is the change in the log or level of the labor market outcome evaluated at the mean for the cell defined by MSA, year, and skill group. The parameter estimates reported in the table are the coefficients on the MSA-time shock for each skill group. The regression also includes intercepts for each skill group capturing average growth rates in the labor market outcome for each skill group. The regression is estimated using nonlinear weighted least squares, using the cell's population as the weight. The sample is from the CPS ORG data and covers 1979–1993. The data are grouped into 2-year periods to increase cell sizes. All labor market outcome variables correspond to the week preceding the interview. For details on sample selection and variable construction, see the text. Standard errors are in parentheses. A ** [*] indicates the parameter is significantly different from 1 at the 1% [5%] level.

for low-skill nonwhite men than the response for high-skill white men. The results for *FT EPOP* (column 2) are generally similar to *Any-work EPOP*. The results for women show that the employment and earnings of high-skill white women exhibit significantly less cyclical fluctuation than any other group, including high-skill white men. This may be due to differences in the industries and occupations that men and women are working in. Alternatively, it may also reflect the fact that women may act as “added workers” who enter the labor force in recessions to make up for lost earnings of the principal earner. These issues will be explored at more length below. Low-skill nonwhite women are the most severely impacted by cycles. The results in columns 1 and 2 show that, for a given shock, their employment rates fluctuate five times as much as those of high-skill white men.

These large parameters for less-educated women are attenuated somewhat when the models are estimated in levels instead of logs. These estimates are shown in columns 3 and 4. As discussed earlier, if the level model is correct, then the low mean employment rate among these groups (*FTYR EPOP* rates for less-educated women are 0.42 for whites and 0.37 for nonwhites) will lead to larger parameters for those groups. Some of these impacts are significant. The most extreme example is the coefficient for low-skill nonwhite women, which is reduced to 1.44 from 5.42 in the *Any-work EPOP* equation. For the remainder of the paper, I rely on the more conservative level equations for EPOP regressions.[16]

The results in column 5 show that the differences across skill groups are smaller when using real weekly earnings. In a given period, the percentage change in real weekly earnings of low-skill white men is 1.2 times as large, and the change for low-skill nonwhite men is about 2 times as large, as that experienced by high-skill white men. This may reflect greater rigidities in wages for low-skill workers. For example, if equilibrium wage rates are driven down in recessions, to the extent that the minimum wage creates a wage floor for low-skill workers, the reduction in earnings for low-wage workers will be

[16]The results for changes in *levels* of earnings generated similar results to changes in *logs*. For the remainder of the study, changes in logs will be used for everything except the EPOP ratios.

smaller, relative to high-skill workers, than their reduction in employment. Alternatively, this may reflect how the composition of workers changes over the business cycle and how this compares across skill groups. This point has been discussed in the empirical literature on cyclical behavior of real wages (for example, see the recent paper by Solon, Barsky, and Parker 1994).

The estimates from pooling the three equations for the ORG data are presented in Table 3. The top portion of the table presents the γ parameters along with their standard errors for each skill group. Note that only one normalization is needed to identify the model. Here we normalize the coefficient for high-skill white men to 1 in the *Any-work EPOP* equation. All of the coefficients are now relative to the effect on *Any-work EPOP* for high-skill white men. Looking across the columns one can see how the fluctuation of one measure compares to another. Overall mean weekly earnings vary the most across the cycle, followed by the *FT EPOP* and then the *Any-work EPOP*. For example, among less-educated nonwhite women, the impact of a shock on mean earnings is about three times as large as the impact on employment rates. To better compare the results to the “single equation” estimates in Table 2, the bottom portion of Table 3 presents the estimates normalized as they are in Table 2. That is, in each column the parameters are divided by the estimated γ for high-skill white men. The statistical significance refers to testing whether these renormalized parameters (in the bottom portion of the table) are significantly different from 1.

When the estimates in the bottom portion of Table 3 are compared with the estimates in Table 2, very similar patterns emerge. Nonwhites and less-educated workers experience fluctuations larger than for other groups. Even within education groups, nonwhites fare worse than whites, possibly reflecting their more disadvantaged status. White women in both high and low education groups experience less cyclical variation than all other groups. Less-educated nonwhite women exhibit more fluctuation, but less than their male counterparts.

TABLE 3
Pooled Regression Results Using CPS ORG
Coefficients on MSA Shock

	(1) *Any-work EPOP (level)*		(2) *FT EPOP (level)*		(3) *Mean Weekly Earnings (log)*	
Coefficients on MSA Shock, by Skill Group						
High educ (>12), white men	1		1.31	(0.20)	2.96	(0.42)
High educ (>12), nonwhite men	1.63	(0.34)	1.88	(0.38)	4.36	(0.80)
High educ (>12), white women	0.60	(0.14)	0.72	(0.15)	2.47	(0.39)
High educ (>12), nonwhite women	1.26	(0.30)	1.11	(0.32)	3.18	(0.68)
Low educ (≤12), white men	1.37	(0.21)	1.64	(0.24)	3.79	(0.52)
Low educ (≤12), nonwhite men	2.92	(0.39)	3.22	(0.43)	6.34	(0.85)
Low educ (≤12), white women	0.80	(0.15)	0.82	(0.16)	2.82	(0.41)
Low educ (≤12), nonwhite women	1.52	(0.25)	1.53	(0.26)	4.56	(0.66)
Coefficients on MSA Shock Relative to Skill Group 1						
High educ (>12), white men	1		1		1	
High educ (>12), nonwhite men	1.63		1.44		1.47*	
High educ (>12), white women	0.60**		0.55**		0.83	
High educ (>12), nonwhite women	1.26		0.84		1.07	
Low educ (≤12), white men	1.37		1.25		1.28*	
Low educ (≤12), nonwhite men	2.92**		2.46**		2.14**	
Low educ (≤12), white women	0.80		0.63**		0.95	
Low educ (≤12), nonwhite women	1.52*		1.20		1.54**	
N	1680		1680		1680	
R^2	0.33		0.33		0.46	

Notes: Each column presents estimates of an equation where the dependent variable is the change in the log or level of the labor market outcome evaluated at the mean for the cell defined by MSA, year, and skill group. The equations are estimated jointly with the MSA shocks common to each equation. The parameter estimates reported in the table are the coefficients on the MSA-time shock for each skill group. The regression also includes intercepts for each skill group capturing average growth rates in the labor market outcome for each skill group. The regression is estimated using nonlinear weighted least squares, using the cell's population as the weight. The sample is from the CPS ORG data and covers 1979–1993. The data are grouped into 2-year periods to increase cell sizes. All labor market outcome variables correspond to the week preceding the interview. For details on sample selection and variable construction, see the text. Standard errors are in parentheses. A ** [*] indicates the parameter is significantly different from 1 at the 1% [5%] level.

All remaining regression models will be estimated using the pooled model. This does not change the qualitative results significantly.

7.2 Results for Annual Measures Using ADF Data

The ADF data allow for two important extensions to the analysis of the ORG data. First, I examine more comprehensive measures of employment corresponding to activities over the past year, thereby getting at changes in the duration and intensity of employment. Second, I can examine family measures in addition to individual measures. The family is the key economic unit and, for policy purposes, an analysis limited to individuals would be incomplete. An analysis of families may differ from one of individuals in that families contain varying numbers of potential workers with differences in propensities for intrafamily substitution of labor market activity.

The results for the ADF are presented in two tables. Table 4 presents the results for individual labor market outcomes (*FTYR EPOP*, annual hours, annual earnings, and hourly wages) and Table 5 presents the results for the family outcomes (head's earnings, spouse's earnings, other family income, and family earnings and income). All results are based on estimates of the pooled model, and the format of the tables is identical to Table 3. The top portion of the table presents the γ parameters along with their standard errors for each skill group. The single normalization in the pooled model is that the coefficient for high-skill white men is normalized to 1 in the *FTYR EPOP* equation. The bottom portion of the table presents estimates with parameters normalized to 1 for the reference group in each equation, thus allowing for easy comparisons across skill groups.

Looking at the top portion of Table 4, the magnitude of changes in annual earnings is larger than annual hours or employment rates. This is not surprising because annual earnings capture changes in employment and hours worked. Average hourly wages (averaged over workers) are, along with the other measures, procyclical. This is consistent with the more recent real wage studies. The bottom portion of Table 4 provides estimates of the relative responsiveness across groups. The responsiveness to a shock is

TABLE 4
Pooled Regression Results Using Individual Measures from CPS ADF
Coefficients on MSA Shock

	(1) FTYR EPOP (level)		(2) Annual Hours (log)		(3) Annual Earnings (log)		(4) Hourly Wage (log)	
Coefficients on MSA Shock, by Skill Group								
High educ (>12), white men	1		1.21	(0.28)	3.24	(0.56)	2.83	(0.54)
High educ (>12), nonwhite men	2.26	(0.50)	2.76	(0.67)	5.03	(1.03)	2.70	(0.94)
High educ (>12), white women	0.02	(0.26)	0.11	(0.21)	1.10	(0.33)	1.02	(0.37)
High educ (>12), nonwhite women	0.96	(0.36)	1.38	(0.51)	2.52	(0.74)	0.77	(0.76)
Low educ (≤12), white men	1.38	(0.26)	1.60	(0.33)	3.38	(0.59)	2.06	(0.49)
Low educ (≤12), nonwhite men	2.82	(0.49)	3.97	(0.70)	6.15	(1.05)	2.10	(0.69)
Low educ (≤12), white women	0.58	(0.17)	1.48	(0.30)	2.86	(0.51)	1.88	(0.44)
Low educ (≤12), nonwhite women	2.04	(0.39)	4.69	(0.78)	7.66	(1.23)	4.01	(0.82)
Coefficients on MSA Shock Relative to Skill Group 1								
High educ (>12), white men	1		1		1		1	
High educ (>12), nonwhite men	2.26**		2.28*		1.55*		0.95	
High educ (>12), white women	0.02**		0.09**		0.34**		0.36**	
High educ (>12), nonwhite women	0.96		1.14		0.78		0.27**	
Low educ (≤12), white men	1.38		1.32		1.04		0.72	
Low educ (≤12), nonwhite men	2.82**		3.28**		1.90**		0.74	
Low educ (≤12), white women	0.58**		1.22		0.88		0.66	
Low educ (≤12), nonwhite women	2.04**		3.88**		2.36**		1.42	
N	2160		2160		2160		2160	
R^2	0.16		0.17		0.29		0.09	

Notes: Each column presents estimates of an equation where the dependent variable is the change in the log or level of the labor market outcome evaluated at the mean for the cell defined by MSA, year, and skill group. The equations are estimated jointly with the MSA shocks common to each equation. The parameter estimates reported in the table are the coefficients on the MSA-time shock for each skill group. The regression also includes intercepts for each skill group capturing average growth rates in the labor market outcome for each skill group. The regression is estimated using nonlinear weighted least squares, using the cell's population as the weight. The sample is from the CPS ADF and covers 1975–1996. The data are grouped into 2-year periods to increase cell sizes. All labor market outcome variables correspond to the week preceding the interview. For details on sample selection and variable construction, see the text. Standard errors are in parentheses. A ** [*] indicates the parameter is significantly different from 1 at the 1% [5%] level.

TABLE 5
Pooled Regression Results Using Family Measures from CPS ADF
Coefficients on MSA Shock

	(1) *Own Earnings (log)*	(2) *Head's Earnings (log)*	(3) *Spouse's Earnings (log)*	(4) *Other Family Income (log)*	*(5) Total Family Earnings (log)*	*(6) Total Family Income (log)*
Coefficients on MSA Shock, by Skill Group						
High ed white men	1	0.94 (0.14)	0.54 (0.19)	1.00 (0.23)	0.81 (0.12)	0.81 (0.11)
High ed nonwhite men	1.35 (0.28)	1.26 (0.28)	1.77 (0.49)	0.59 (0.53)	1.32 (0.24)	1.17 (0.22)
High ed white women	0.34 (0.10)	0.86 (0.13)	0.23 (0.18)	1.23 (0.24)	0.72 (0.11)	0.75 (0.10)
High ed nonwhite women	0.84 (0.24)	0.97 (0.24)	1.85 (0.45)	1.44 (0.49)	1.33 (0.23)	1.25 (0.21)
Low ed white men	0.94 (0.15)	0.92 (0.14)	0.92 (0.22)	0.57 (0.24)	0.92 (0.13)	0.82 (0.12)
Low ed nonwhite men	1.50 (0.23)	1.35 (0.22)	2.51 (0.41)	1.36 (0.40)	1.74 (0.23)	1.48 (0.20)
Low ed white women	0.83 (0.13)	0.87 (0.13)	1.22 (0.22)	0.87 (0.23)	0.98 (0.13)	0.91 (0.12)
Low ed nonwhite women	2.18 (0.27)	1.88 (0.25)	3.91 (0.49)	1.50 (0.38)	2.49 (0.28)	1.99 (0.22)
Coefficients on MSA Shock Relative to Skill Group 1						
High ed white men	1	1	1	1	1	1
High ed nonwhite men	1.35	1.34	3.28*	0.59	1.63*	1.44
High ed white women	0.34**	0.91	0.43	1.23	0.88	0.93
High ed nonwhite women	0.84	1.03	3.42**	1.44	1.64*	1.54
Low ed white men	0.94	0.98	1.70	0.57	1.14	1.01
Low ed nonwhite men	1.50**	1.44*	4.64**	1.36	2.15**	1.83**
Low ed white women	0.83	0.93	2.26**	0.87	1.21	1.12
Low ed nonwhite women	2.18**	2.00**	7.24**	1.50	3.07**	2.46**
N	2160	2160	2160	2160	2160	2160
R^2	0.22	0.31	0.31	0.19	0.13	0.03

Notes: Each column presents estimates of an equation where the dependent variable is the change in the log of the labor market outcome evaluated at the mean for the cell defined by MSA, year, and skill group. The equations are estimated jointly with the MSA shocks common to each equation. The parameter estimates reported in the table are the coefficients on the MSA-time shock for each skill group. The regression also includes intercepts for each skill group capturing average growth rates in the labor market outcome for each skill group. The regression is estimated using nonlinear weighted least squares, using the cell's population as the weight. The sample is from the CPS ADF and covers 1975–1996. The data are grouped into 2-year periods to increase cell sizes. All labor market outcome variables correspond to the week preceding the interview. For details on sample selection and variable construction, see the text. Standard errors are in parentheses. A ** [*] indicates the parameter is significantly different from 1 at the 1% [5%] level.

higher for those with lower educational levels and nonwhites, and lower for more-educated white women. The results are particularly striking when less-educated white and nonwhite groups are compared. For both men and women, nonwhites are significantly more impacted by business cycles than whites are. For example, the equation for mean annual hours worked shows that less-skilled white men are 1.3 times more affected than more-skilled white men, while less-skilled nonwhite men are more than 3 times more affected.[17]

The results for earnings show smaller differences across groups than the employment measures. This is also found in the ORG data. Again, this may reflect differences across groups in the types of workers who experience unemployment (or reductions in hours) or differences in wage rigidities between high- and low-skill workers. This can be examined more directly by looking at the estimates for the equation for average hourly wages (column 4). The adjusted parameters in the bottom half of the table are mostly less than 1, which implies that the cyclical fluctuations in the wages of high-skill white men are larger than those for nonwhites, women, and less-skilled workers. This dampens the differences across groups in annual earnings.

The estimates for the pooled models of family outcomes are presented in Table 5. Family income is disaggregated into head's earnings, spouse's earnings, and other family income, as well as total family earnings and income.[18] Other family income includes transfers, capital income, and earnings of other family members. Individual annual earnings are also included to provide some reference to the earlier tables on individual outcomes.[19] Examining the top portion of Table 5 shows that the earnings of heads

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[17]We also estimated models with *Any-work EPOP*. Those estimates show large but no statistically significant differences across groups.

[18]For the purposes of this analysis, the "head" is defined as either the head of the CPS family or subfamily (if the person is part of a family) or an individual if he/she is an unrelated person or a secondary individual. In married couples, the man is assigned to be the head. If there is no spouse in the family, a value of 0 is used for spouse earnings.

[19]Note that the parameter estimates for individual earnings in Table 5 do not match exactly the parameters in Table 4. That is because a different set of equations were estimated, thus generating somewhat different estimated MSA shocks. The coefficients are quite comparable.

are less variable than individual earnings. Comparing head's earnings (column 1) to family earnings (column 5) shows that in the most disadvantaged groups (nonwhite and less-educated) there is little evidence of labor substitution among family members as family earnings fluctuate more than head's earnings. Among high-skilled families (more-educated whites), family earnings fluctuate less than head's earnings. That can be seen more directly by the small coefficient on spouse's earnings for more-educated white groups. Transfers tend to reduce the size of the shock, which can be seen by comparing the estimates for family earnings and family income.

By examining the bottom portion of the table, with parameters normalized to 1 for the reference group in each equation, one can compare how the different family measures impact groups differentially. In general, these figures match the general pattern of findings thus far. Those with lower educational levels and nonwhites show greater responsiveness to cycles than the high-skill and white groups do. The most striking results exist for spouse's earnings, with much greater fluctuations for less-educated nonwhite, and to a lesser extent white, individuals. This is in part due to lower marriage rates in these groups, but may also reflect differences in the propensity for women to be "added workers."

Including nonlabor income has a significant impact on the differences in cyclical responses across skill groups. In general, the gaps between groups narrow when considering family income (column 6). This pattern was also found by Blank (1989) and Blank and Card (1993). The reduction in volatility is especially evident for less-skilled nonwhite individuals. For example, family earnings of less-educated nonwhite women fluctuate 3 times as much as the reference group, but their family income fluctuates only 2.5 times as much as the income of the reference group. This is a 15 percent reduction. In analyses not shown here, the reduction in the impact of cycles on low-skill families comes from receipt of countercyclical government transfers such as welfare and unemployment assistance.[20]

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[20]I explored estimating models with more disaggregated measures of nonlabor income such as public assistance. In practice, few families receive these transfers and most of the parameters were not statistically significant.

7.3 Discussion

The results from the analysis of the ORG and ADF data show consistently that, relative to high-skill white men, nonwhites and those with low educational levels have greater fluctuation in cycles. Highly educated white women are the only group that consistently shows lower responsiveness compared with the reference group. Here we explore why. First, some groups may be less tied to the labor market and may rely on government transfers or the labor earnings of other family members. Another hypothesis is that the jobs held by individuals in these groups vary in ways that would lead to expected differences in employment fluctuations. It is fairly well established that construction and manufacturing jobs—as well as jobs for laborers, younger workers, and those in nonunion employment—experience more employment fluctuations, while jobs in the public and FIRE (finance, insurance, and real estate) sectors, managerial jobs, and union jobs experience less employment fluctuations.

These possibilities are explored in Table 6, which presents means of some of these variables for each of the skill groups used in the analysis. The patterns in the table match in many ways the patterns found in the regressions. For example, highly educated white women, the least responsive group, are least likely to be in construction and manufacturing and are much more likely to be in retail trade, FIRE, and public sector jobs. They are also more likely to be in managerial and professional jobs and less likely to be in operator/laborer positions. Less-educated nonwhite men, a group with relatively high cyclical responsiveness, are most represented in construction, manufacturing, and laborer positions, and have the lowest union participation rates. This simple analysis gives mixed evidence for less-skilled nonwhite women, who were found in the regression analysis to be the most responsive group. On the one hand, they have the highest rates of nonattachment to the labor market and highest welfare reliance, which would suggest smaller cyclical fluctuations. On the other hand, those who are employed are more likely to be in manufacturing and in laborer positions, which would lead to higher rates of cyclical fluctuation.

TABLE 6
Means of Selected Characteristics by Skill Group, 1998 CPS ADF

	High Education (>12)				Low Education (≤12)			
	Men		Women		Men		Women	
	White	Nonwhite	White	Nonwhite	White	Nonwhite	White	Nonwhite
Age	43.7	38.7	43.3	37.9	43.3	37.3	47.9	40.7
Head earnings/family income (%)	66%	63%	60%	60%	59%	59%	54%	54%
Spouse earnings/family income (%)	17%	17%	19%	17%	17%	14%	16%	11%
Welfare income/family income (%)	0%	0%	0%	2%	0%	2%	2%	7%
Other transfers/family income (%)	7%	9%	9%	11%	13%	11%	16%	15%
Any work EPOP	0.93	0.89	0.82	0.82	0.86	0.80	0.67	0.58
FTYR EPOP	0.77	0.82	0.53	0.58	0.68	0.61	0.42	0.37
Union (%)	42%	30%	40%	35%	38%	27%	40%	30%
Industrial Composition								
Construction (%)	6.1%	5.2%	1.2%	0.6%	15.2%	12.9%	1.3%	0.8%
Manufacturing (%)	19.0%	16.4%	7.7%	7.3%	23.2%	22.2%	13.2%	18.2%
Retail trade (%)	12.6%	13.6%	13.7%	14.1%	19.6%	20.6%	28.9%	22.5%
FIRE (%)	6.7%	5.3%	8.8%	9.5%	2.3%	2.4%	7.8%	4.9%
Public administration (%)	7.3%	9.7%	5.1%	7.3%	2.9%	2.0%	3.4%	3.2%
Occupational Composition								
%Managerial/professional	43.8%	30.6%	46.7%	35.8%	7.8%	3.9%	11.5%	6.5%
%Technical/sales/administrative	23.5%	24.2%	38.7	44.5%	15.6%	11.9%	48.0%	34.2%
%Service occupations	22.2%	28.0%	12.0%	15.1%	45.4%	48.5%	29.1%	40.1%
%Operators/laborers	10.4%	17.2%	2.7%	4.6%	31.3%	35.6%	11.5%	19.3%
Number of observations	15207	2937	17398	4020	15855	7378	19048	8452

Note: Means apply to the sample of persons working as of the survey week.

7.4 Extensions

All of the regression results hold the skill group responsiveness to be fixed over the entire period of the study. The two major business cycles covered in the data, the 1982 and 1992 recessions, differed a great deal in which industries and occupations were most impacted. Farber (1997), using data from the Displaced Worker Surveys, shows that in the early 1990s displacement rates among more highly educated workers increased relative to those with lower educational levels. The impacts of changes over time in the relative responsiveness is explored in this section using the ADF data. First, graphs comparing more- and less-educated men are presented for the 1989–1992 period, which can be compared with the earlier graphs for 1979–1982. Second, the regressions are estimated allowing for different skill group parameters for 1975–1988 versus 1990–1996.

Figure 6 presents changes between 1989 and 1992 in the log of mean annual hours and earnings for less-skilled men compared with the reference group, more-skilled white men. Comparing this with Figure 5, the comparable figure for 1979–1982, several important differences emerge. First, in the 1992 recession the effect of the downturn on the low-skill group is much closer to the effect on the high-skill group. The MSA observations are clustered much closer to the 45 degree line (the line of equal effects). Second, this feature is found for both whites and nonwhites, although more so for whites.

This is explored further in Table 7, which reports results for equations for individual earnings, family earnings, and family income and uses the same pooled model as above. The only difference is the addition of a set of skill-group-specific cycle parameters that apply to the post-1988 period:

$$\Delta \ln(y_{jmt}) = \alpha_j + (\gamma_j + \gamma_{1j} * Post88_t)\, \beta_{mt} + \varepsilon_{jmt} \ . \qquad \textbf{(4)}$$

The coefficients γ_{1j} represent the change in the responsiveness between the early and later periods. The break year is 1988 because it is the end of the recovery from the 1982 recession. The top portion of the table presents the cyclical responsiveness parameters for the overall period (γ_j), and the bottom portion

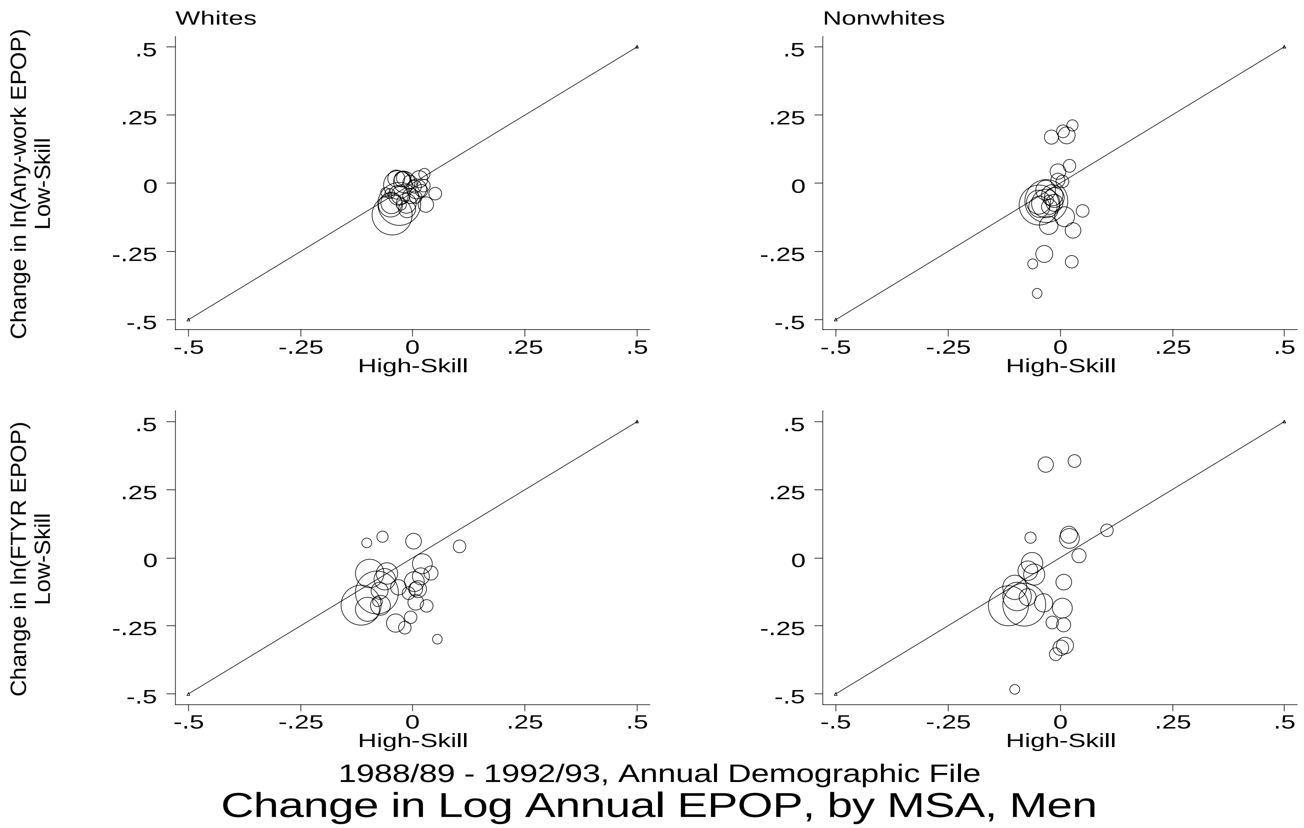
Whites
Nonwhites
Change in ln(Any-work EPOP)
Low-Skill
Change in ln(FTYR EPOP)
Low-Skill
.5
.25
0
-.25
-.5
High-Skill
1988/89 - 1992/93, Annual Demographic File
Change in Log Annual EPOP, by MSA, Men

Figure 6

TABLE 7
Pooled Regression Results Using Family Measures from CPS ADF
Allowing for Changes in Parameters over Time

	(1) *Own Annual Earnings (log)*		(2) *Total Family Earnings (log)*		(3) *Total Family Income (log)*	
Coefficients on MSA Shock, by Skill Group	*All Years*					
High educ (>12), white men	1		0.80	(0.18)	0.76	(0.16)
High educ (>12), nonwhite men	2.02	(0.51)**	1.90	(0.45)**	1.70	(0.40)**
High educ (>12), white women	0.85	(0.20)	0.77	(0.18)	0.76	(0.17)
High educ (>12), nonwhite women	1.61	(0.44)	1.69	(0.40)*	1.67	(0.38)**
Low educ (≤12), white men	1.25	(0.25)	1.10	(0.21)	0.93	(0.18)
Low educ (≤12), nonwhite men	2.14	(0.42)**	2.38	(0.42)**	1.97	(0.36)**
Low educ (≤12), white women	1.06	(0.21)	1.12	(0.21)	0.94	(0.18)
Low educ (≤12), nonwhite women	2.39	(0.43)**	2.60	(0.44)**	2.09	(0.36)**
Coefficients on MSA Shock by Skill Group	*Post-1988*					
High educ (>12), white men0	0		-0.03	(0.21)	-0.04	(0.19)
			0.00		*0.00*	
High educ (>12), nonwhite men	-0.96	(0.56)	-1.15	(0.48)**	-1.09	(0.43)**
			-1.12		*-1.05*	
High educ (>12), white women	-0.69	(0.22)**	-0.09	(0.20)	-0.12	(0.19)
			-0.06		*-0.08*	
High educ (>12), nonwhite women	-1.28	(0.48)**	-0.83	(0.44)	-0.92	(0.40)*
			-0.80		*-0.88*	
Low educ (≤12), white men	-0.30	(0.29)	-0.28	(0.25)	-0.23	(0.21)
			-0.24		*-0.19*	
Low educ (≤12), nonwhite men	-0.81	(0.46)	-1.25	(0.45)**	-1.12	(0.38)**
			-1.22		*-1.08*	
Low educ (≤12), white women	-0.49	(0.24)	-0.24	(0.24)	-0.13	(0.21)
			-0.21		*-0.09*	
Low educ (≤12), nonwhite women	-0.58	(0.49)	-0.48	(0.50)	-0.46	(0.41)
			-0.44		*-0.42*	
N	2160		2160		2160	
R^2	0.30		0.37		0.34	

Notes: Each column presents estimates of an equation where the dependent variable is the change in the log of the labor market outcome evaluated at the mean for the cell defined by MSA, year, and skill group. The equations are estimated jointly with the MSA shocks common to each equation. This specification allows the effects of MSA shocks to differ over the period. The top panel presents estimates corresponding to the full period and the bottom presents estimates for the post-1988 period. The numbers in italics in the bottom panel represent the changes in the skill group coefficient in the post-1988 period relative to the change for skill group 1. Standard errors are in parentheses. In the top panel, a ** [*] indicates the parameter is significantly different from 1 at the 1% [5%] level. In the bottom panel, a ** [*] indicates that the parameter is significantly different from 0 at the 1% [5%] level.

presents the parameters for the difference between the pre- and post-1988 periods (γ_{1j}). Two normalizations are needed to estimate the pooled model. As above, the coefficient for high-skill white men in the overall period is normalized to 1. In addition, the parameter capturing differences between the pre- and post-1988 period is set to 0 for this group. In the bottom of the table, all coefficients are also renormalized by subtracting the value for the reference group, as shown in italics. For the statistical significance tests, the top panel figures are different from 1 and the bottom panel figures are different from 0.

These results fairly consistently show that the relative responsiveness of cycles by the low-skill groups has declined relative to high-skill white men over this period. That is, all coefficients are negative in the bottom of the table. This is consistent with Farber (1997).[21] The largest reductions occur for the most disadvantaged groups. For example, referring to the results for annual earnings, the relative responsiveness of less-skilled nonwhite men fell by −0.81. The relative responsiveness of family income fell by −1.08 from an overall level of 2.09 for less-educated nonwhite men The table indicates that many of these reductions are statistically significantly different from zero. The reductions for low-skill nonwhite women were not as large. Overall, these results show that the 1992 recession was much more skill-group-neutral than the 1982 recession.[22]

Several sensitivity tests were performed for these models. In all cases, specific parameters changed somewhat but the qualitative results were the same. Changing the definition of race from white/non-Hispanic and black/Hispanic to white and black led to larger racial differences. Hispanic men appear to be more like whites in that they have relatively high employment rates and relatively less cyclical variation. They also have relatively low educational levels, so they are a sizable fraction of the

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[21]Bartik (1996) finds no evidence of changes over time. Bartik’s sample, however, ends in 1987, which is likely to be before the changes started taking place.

[22]We, of course, cannot conclude that this is evidence that future recessions will be more skill-group-neutral. There are only two recessions in the data, and these results could be driven by something specific to the 1992 recession that is unlikely to be replicated.

less-educated nonwhite group. Expanding the skill groups by considering four education groups led to larger differences between education levels. However, the precision of the estimates declined somewhat and many of the differences were not statistically significant.[23]

8. CONCLUSION

This paper uses data from the CPS covering the period 1975–1997 to examine how business cycles impact the employment, earnings, and income of low-skill groups relative to high-skill groups. The results consistently show that those with lower educational levels, nonwhites, and low-skill nonwhite women are more impacted by cycles than are high-skill white men. The analysis of family income shows evidence that government transfers are effective at narrowing the differences in impacts across demographic groups.

The results suggest that a 1 percentage point increase in the employment rate of highly educated white men is accompanied by a 2.92 percentage point increase in the employment rate for less-educated nonwhite men and a 1.5 percentage point increase in the employment rate for less-educated nonwhite women. Total annual family earnings of less-educated nonwhite men (women) are expected to fluctuate 2 times (3 times) as much as the fluctuation for highly educated white men. Total family income is somewhat more neutral across groups, with relative responses of less-educated nonwhite men and women of 1.8 and 2.5, respectively.

[23]Other specification tests included (1) limiting the MSA sample to the largest 15–20 MSAs, (2) dropping "seam" years when the MSA boundaries change, and (3) dropping the 1995 and 1996 ADF years when the topcode on earnings increased significantly. The results were not sensitive to changing the MSA sample or dropping the seam years. Dropping the most recent ADF years did lead to modest increases in the relative responsiveness of the earnings and income of low-skill groups. Looking back at Figure 2b, the earnings of more-educated white men increased significantly with the increase in topcodes in 1995. Given that this was in a recovery, dropping those years leads to larger differences in the cyclical variation across skill groups.

The results also suggest that the 1992 recession and subsequent recovery had differential impacts compared with the 1982 recession and recovery. In particular, in the 1989–1996 period, the sensitivity to cyclical variation of less-skilled groups was still larger than that of high-skill groups, but the differences narrowed. This may be due in part to the fact that the less-skilled groups had somewhat low employment rates going into the 1992 recession. It may also reflect differences in the industries that were affected in the 1992 versus 1982 recessions. Identifying the sources of this change is important and should be examined in future work.

Welfare reform is generating a flow of less-skilled workers into the labor market. This study highlights the importance of thinking ahead toward the next recession and its impacts on less-skilled workers. The effects could be very adverse if these relatively new labor market entrants have exhausted their AFDC time limits and have incomplete coverage in the unemployment insurance program. This suggests policies aimed at making sure that unemployment insurance reaches these new entrants, and at extending time limits in the event of adverse state labor market conditions.

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